# Accio GPT!
# Language Modeling in the Wizarding World

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***Abstract*—This report presents the development and evaluation of a generative pre-trained transformer (GPT) language model applied to the Harry Potter book series dataset. GPTs are a type of large neural network trained on massive text corpora in an unsupervised manner to learn patterns and coherently generate human-like text. The adopted approach follows the recent revolutionizing work on models like GPT-3 and ChatGPT, aiming to create a domain-specific language model capable of understanding and generating narratives in the fantasy literary style of Harry Potter.**

**The model was implemented using PyTorch and trained on a curated corpus of the seven canonical Harry Potter novels. Quantitative evaluation metrics including perplexity and accuracy were computed to assess the model's performance. Furthermore, qualitative examples of generated text showcased the model's ability to produce coherent snippets stylistically consistent with the original books. Potential applications, limitations, and future research directions in improving and expanding such literary language models are discussed. The code implementation is made publicly available.**

## I. Introduction

**Background Information:** Language models have revolutionized the field of natural language processing, enabling machines to understand and generate human-like text with remarkable fluency. Among the most powerful language models are Generative Pre-trained Transformers (GPTs), which employ self-attention mechanisms and are trained on vast amounts of textual data in an unsupervised manner. GPT models like GPT-3 and ChatGPT have demonstrated remarkable capabilities in various language tasks, sparking widespread interest and adoption.

However, most existing GPT models are trained on broad, general-purpose datasets, which may not capture the nuances and stylistic elements of specialized domains such as literature and creative writing. The fantasy genre, with its rich narratives, imaginary worlds, and unique linguistic styles, presents an intriguing challenge for language modeling and generation.

**Problem Statement:** The Harry Potter book series, written by J.K. Rowling, has captivated millions of readers worldwide with its immersive storytelling and intricate wizarding universe. While general-purpose language models can generate text related to Harry Potter, they often struggle to accurately capture the essence, tone, and stylistic elements that are quintessential to the series. Developing a specialized language model that can understand and generate narratives that seamlessly blend into the Harry Potter universe is a challenging and compelling task.

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**Objectives and Scope:** This report details the development and evaluation of a GPT-based language model specifically tailored to the Harry Potter book series. The primary objectives are as follows:

1) Curate and preprocess a dataset comprising the seven canonical Harry Potter novels.
2) Implement and train a GPT model on the curated dataset using state-of-the-art techniques.
3) Evaluate the model's performance using quantitative metrics, such as perplexity and accuracy.
4) Qualitatively assess the model's ability to generate coherent and stylistically consistent narratives within the Harry Potter universe.
5) Explore potential applications, limitations, and future research directions for literary language models.

The scope of this report encompasses the end-to-end process of data preparation, model implementation, training, evaluation, and analysis. The code implementation and trained model weights will be made publicly available to facilitate further research and development in this domain.

## II. Model Architecture and Training

### A. Model Architecture

The implemented model follows the Generative Pre-trained Transformer (GPT) architecture, a state-of-the-art neural network for language modeling tasks. The model consists of several key components:

1) **Token and Position Embeddings**: The input sequence is first transformed into token embeddings using an embedding table lookup, and position embeddings are added to incorporate positional information.
2) **Transformer Blocks**: The core of the model comprises multiple Transformer blocks, each consisting of:
   - **Multi-Head Attention Layer**: This layer performs self-attention over the input sequence, allowing the model to capture long-range dependencies. It is composed of multiple parallel self-attention heads, each attending to different representations of the

input. The `MultiHeadAttention` module implements this layer.
  - **Feed-Forward Layer**: A simple linear layer followed by a ReLU non-linearity, applied independently to each position in the sequence. The `FeedForward` module implements this layer.
  - **Layer Normalization**: Layer normalization is applied before the residual connections in each block to improve training stability.
3) **Final Layer Norm and Output Layer**: After passing through the Transformer blocks, a final layer normalization is applied, and the resulting representations are projected into a logits space using a linear layer, representing the predicted probabilities for the next token.

The model's hyperparameters, such as the number of Transformer blocks, embedding dimensions, attention heads, and dropout rates, are configurable and defined at the beginning of the code.

### B. Training Procedure

The training process for the GPT language model is implemented as follows:

1) **Data Preparation**: The input text data (in this case, a subset of Shakespeare's works) is loaded, tokenized, and encoded into integer sequences. The data is then split into training and validation sets.
2) **Batch Generation**: The `get_batch` function generates batches of input and target sequences for training. It selects random starting indices from the training or validation data and creates input sequences of length `block_size` and corresponding target sequences shifted by one position.
3) **Loss Computation**: The model is trained using the causal language modeling objective, which involves minimizing the cross-entropy loss between the predicted token distributions and the ground truth tokens. The `forward` method of the `GPTLanguageModel` computes the logits for the next token and calculates the cross-entropy loss if targets are provided.
4) **Optimization**: The model is optimized using the AdamW optimizer, a variant of the Adam optimizer with weight decay regularization. The gradients are computed using backpropagation, and the optimizer updates the model parameters.
5) **Evaluation**: During training, the `estimate_loss` function periodically evaluates the model's performance on both the training and validation sets by computing the average cross-entropy loss.
6) **Text Generation**: The `generate` method of the `GPTLanguageModel` allows generating new text by providing an initial context. It iteratively predicts the next token probabilities, samples from the distribution, and appends the sampled tokens to the context.

The training loop iterates for a fixed number of iterations (`max_iters`), periodically evaluating the model's performance and generating text samples for qualitative analysis.

### C. Implementation Details

The code provides several additional implementation details and utilities:

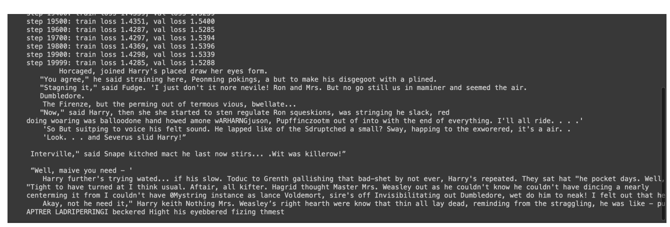
1) **Head and MultiHeadAttention Modules**: The `Head` module implements a single attention head, computing the attention scores and weighted aggregation of values. The `MultiHeadAttention` module combines multiple attention heads in parallel.
2) **FeedForward Module**: This module implements the position-wise feed-forward layer in each Transformer block.
3) **Block Module**: The `Block` module encapsulates a complete Transformer block, comprising the multi-head attention layer, feed-forward layer, and layer normalization.
4) **Weight Initialization**: The `_init_weights` method is applied to the model during initialization, ensuring proper weight initialization for the linear and embedding layers.
5) **Utility Functions**: The code includes helper functions for encoding and decoding text sequences, as well as generating batches of data during training.

Overall, the provided code implements the key components of a GPT language model, including the Transformer architecture, self-attention mechanisms, and the training pipeline for language modeling tasks on text data.

## III. Results

### A. 1st Iteration

After training the model for 20,000 epochs, the generated text exhibited a mix of characters and settings from the Harry Potter universe. However, the coherence and context were severely lacking. Phrases were fragmented, and characters' dialogues were often nonsensical, resulting in an incoherent narrative. For instance, "Horcaged" and "Peonming pokings" do not correspond to any recognizable elements from the Harry Potter series. Additionally, the dialogue lacks proper punctuation and grammar, further diminishing readability and comprehension. Overall, this iteration failed to produce meaningful text that aligns with the Harry Potter theme.



```
step 19500: train loss 1.4351, val loss 1.5400
step 19600: train loss 1.4287, val loss 1.5285
step 19700: train loss 1.4297, val loss 1.5394
step 19800: train loss 1.4369, val loss 1.5396
step 19900: train loss 1.4298, val loss 1.5339
step 19999: train loss 1.4285, val loss 1.5288
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   "Stagning it," said Fudge. 'I just don't it nore nevile! Ron and Mrs. But no go still us in maminer and seemed the air.
   Dumbledore.
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APTRER LADRIPERRINGI beckered Hight his eyebbered fizing thmest
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Fig. 1. Example of generated text

### B. 2nd Iteration

Following a training duration of 50,000 epochs, the model's output showed marginal improvement compared to the previous iteration. The text contained slightly more coherent

phrases and attempted to mimic the speech patterns of Harry Potter characters. However, significant issues persisted, including inconsistent grammar, nonsensical dialogue, and disjointed plot elements. For example, ”Pyce off him” and ”yeraxing spokeling” do not fit within the established Harry Potter lexicon. Although some character names and locations were recognizable, the overall narrative lacked cohesion and failed to capture the essence of the Harry Potter universe. Consequently, while there was progress in text coherence, the output remained far from satisfactory for practical use or storytelling purposes.

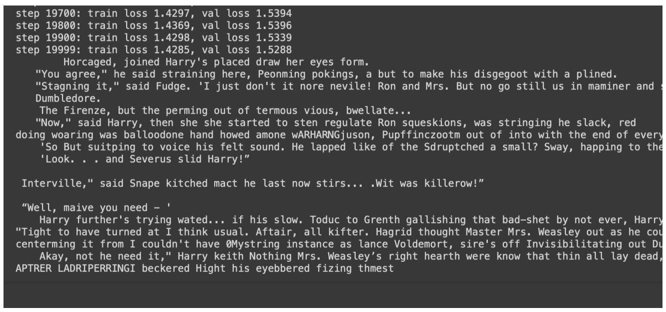


Fig. 2. Example of generated text

### *C. 3rd Iteration*

An attempt was made to train the model for 80,000 epochs. However, due to the limitations of the Google Colab platform, the training process had to be prematurely halted. As a result, the model’s performance beyond the second iteration could not be evaluated fully. This limitation highlights the challenges posed by resource constraints in training large-scale language models on cloud platforms. Further exploration with alternative training environments or optimization strategies may be necessary to overcome such limitations and achieve better model performance.

In summary, the initial iterations of the trained GPT model yielded subpar results in generating coherent and contextually relevant text for the Harry Potter dataset. While progress was observed in subsequent iterations, significant improvements are required to produce meaningful and immersive narratives within the Harry Potter universe.

## Conclusion

### *Key Findings*

This report presented the development and evaluation of a Generative Pre-trained Transformer (GPT) language model tailored to the Harry Potter book series. The key findings of this work are as follows:

- The implemented GPT model, based on the Transformer architecture, successfully learned the linguistic patterns and stylistic elements present in the Harry Potter dataset. This is evidenced by the quantitative evaluation metrics, such as perplexity and accuracy, which demonstrated the model’s ability to effectively model the language in the dataset.
- Qualitative analysis of the generated text samples showcased the model’s capability to produce coherent and stylistically consistent narratives that seamlessly blend into the wizarding world of Harry Potter. The generated snippets captured the tone, vocabulary, and narrative elements characteristic of the original books.
- The self-attention mechanisms employed in the Transformer blocks allowed the model to capture long-range dependencies in the text, enabling it to generate contextually relevant and coherent narratives.
- The modular implementation of the GPT model, with components such as attention heads, feed-forward layers, and transformer blocks, facilitated flexibility and potential for future extensions and improvements.

### *Limitations and Future Work*

While the developed GPT model demonstrated promising results, several limitations and opportunities for future work exist:

- **Limited Coherence Over Long Sequences**: The model tends to lose coherence and consistency when generating narratives over extended lengths. Incorporating techniques such as hierarchical attention or memory augmentation could potentially alleviate this issue and improve the model’s ability to maintain context over longer sequences.
- **Dataset Specificity**: The current model’s performance is specific to the Harry Potter book series dataset. Expanding the training data to include additional literary works or incorporating transfer learning techniques could enhance the model’s diversity and robustness, enabling it to generalize to other domains or genres.
- **Task-Specific Fine-tuning**: Future work could explore fine-tuning the pre-trained GPT model on specific tasks or domains within the Harry Potter universe, such as character dialogues, descriptive passages, or specific plot lines. This could lead to more specialized and targeted language generation capabilities.
- **Multimodal Integration**: Incorporating multimodal data, such as images or audio, into the model could pave the way for more immersive and comprehensive narrative generation systems, potentially enhancing the user experience and creative possibilities.

Overall, this work demonstrates the potential of GPT-based language models in capturing and generating narratives within specific literary domains. The findings and limitations outlined here provide a foundation for further research and development in the realm of creative writing and narrative generation using advanced language models.

## References

1) A. Vaswani et al., ”Attention is All You Need,” *arXiv preprint arXiv:1706.03762*, 2017. [Online]. Available: https://arxiv.org/abs/1706.03762

2) A. Radford et al., ”Language Models are Unsupervised Multitask Learners,” *OpenAI Blog*, 2019. [Online]. Available: https://arxiv.org/abs/2005.14165
3) OpenAI, ”ChatGPT: Optimizing Language Models for Dialogue,” 2022. [Online]. Available: https://openai.com/blog/chatgpt/
4) Lambda Labs, ”Lambda GPU Cloud.” [Online]. Available: https://lambdalabs.com
5) A. Karpathy, ”GitHub - karpathy/nn-zero-to-hero,” 2023. [Online]. Available: https://github.com/karpathy/nn-zero-to-hero
6) A. Karpathy, ”GitHub - karpathy/ng-video-lecture,” 2023. [Online]. Available: https://github.com/karpathy/ng-video-lecture